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Impacts of irrigation efficiency on agricultural water-land nexus system management under multiple uncertainties—A case study in Amu Darya River basin, Central Asia

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ABSTRACT

Water and land are the two most critical resources for food production and they are intricately linked. Irrigation expansion, population growth, and climate change are threatening the sustainability of water-land nexus system (WLNS). In this study, a possibilistic-flexible chance-constrained programming (PFCP) method that is capable of addressing multiple uncertainties expressed as possibilistic distributions, flexible variables, and probabilistic distributions existed in WLNS is developed. PFCP can help gain in-depth analysis of the tradeoffs between system benefit and reliability of satisfying constraints. Then, the proposed PFCP method is applied to the lower reaches of Amu Darya River basin for assessing the impact of irrigation efficiency on the WLNS management, where 1080 scenarios are analyzed in association with different irrigation schemes, violation risk levels, and satisfactory degrees. A number of water and land resources allocation alternatives for different irrigation districts and crops are generated. Results indicate that the advanced irrigation modes (e.g., sprinkle and drip) can improve irrigation efficiency and raise unit water benefit from 0.15 US$/m^3 to 0.24 US$/m^3. Irrigation mode with efficiency of about 0.61 is an effective option in adaption to changed water availabilities, which is beneficial for pursuing balance between water and land relationships. These findings can support decision makers implementing comprehensive agricultural management strategies (e.g., the advancement of irrigation modes as well as the optimization of water and land allocation patterns) in responding to variations in water availability, electricity consumption, and market price.

1. Introduction

1.1. Importance

Water and land are the two most critical resources for food production. In recent years, the land and water resources for agricultural activities are facing with a number of problems due to the rapid growth of population, development of urbanization and spread of pollution (Das et al., 2015). According to FAO (2013), global per capita agricultural land is about 0.7 ha, only 37.9% of per capital land area. Meanwhile, global per capital freshwater withdrawal amounts to 552.1 m^3 per year, nearly 70% is attributed to agricultural use (Chen et al., 2018). However, only 50% of agricultural water resources is estimated to be consumed by crops; the remainder is lost during storage, conveyance, and sub-surface drainage after application (Al-Faraj et al., 2016). Especially, water losses are more enormous (as high as 60%) in Central Asia because of outdated infrastructure and the dominance of highly inefficient flood and furrow irrigation techniques (Bekchanov et al., 2016).

In the real-world problems, agricultural water and land resources are intricately linked; the utilization of them is significantly affected by specific limitations associated with individual conditions and the constraints imposed by their interactions. On one hand, water resources is a pre-requisite for agricultural land uses requiring irrigation (Singh, 2015). The amount of water resources would direct or indirect influence the areas of land cultivation and irrigation. On the other hand, agricultural land-use expansion can alter water-flow regime, affect water availability, and intensify water demand (Weatherhead and Howden, 2009). As a result, extensive water withdrawal for agricultural land would result in water scarcity and enlarge the competition among different water users (Gheewala et al., 2018). It is reported that agricultural production requirements of the burgeoning global population

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are expected to increase by about 50% in 2050 (McClymon et al., 2019). This task seems to be challenging in the context of scarcity of land and water resources caused by speedy urbanization and severe climate change, particularly in arid and semi-arid regions (e.g., Central Asia). Therefore, it is desired to co-manage water and land resources and plan water-land nexus system (WLNS).

1.2. Literature review

Previously, a number of research works focused on seeking sustainable solutions to WLNS management; increased water use efficiency seems to be a promising strategy (Nazari et al., 2018; Malek and Verburg, 2018; Sun et al., 2018). Das et al. (2015) developed a linear programming model for land and water resources allocation in eastern India with consideration of canal conveyance and field application efficiencies, which suggested that irrigation efficiencies would largely influence resources allocation patterns. Fu et al. (2018) investigated water saving potential of an irrigation area based on an evapotranspiration model; results showed that irrigation efficiency was positively correlated with precipitation and negatively correlated with the net irrigation water volume. Malek and Verburg (2018) developed a global land system model for exploring the significant adaptation options for land management with constraints of water availability; results indicated that no or low irrigation efficiency improvements led to a reduction in irrigated areas. Mirshadiev et al. (2018) advanced a strength, weakness, opportunity, and threat framework for identifying the promising land management and water use practices, where the impacts of different irrigation modes with varied efficiencies on crop yield were investigated. The above studies show that improving water use efficiency are efficient practices for reducing the volume of water applied to agriculture and increasing crop yields (Koopman et al., 2017). However, most of these studies mainly focused on managing WLNS in a deterministic framework; there is a gap between the recognition of uncertainty's importance and its actual incorporation in models.

WLNS is often associated with multiple resources (e.g., water and land), multiple irrigation modes (e.g., furrow, sprinkle and drip), and multiple crops (e.g., cotton, vegetable and grain). Such a complex system as well as inextricable interactions among subsystems enlarges the difficulties for exploring irrigation efficiency's impact on WLNS management. The system is also plagued with uncertainties due to inexact information, natural process, and human subjectivity (Li et al., 2009). For example, available water resources are influenced by random events such as precipitation and evaporation, which are represented as a probability distribution around the actual streamflow (Li et al., 2017). All these uncertainties bring great challenges to decision makers for identifying efficient water-land management strategies. In response to such complexities and uncertainties, more robust system analysis techniques are desired.

Stochastic optimization methods were proposed for dealing with problems with known probability distributions in the agricultural management system (Guo et al., 2014; Khandelwal and Dhiman, 2018). Singh (2015) developed a chance-constrained programming (CCP) model for the seasonal optimal allocation of available land and water resources, where the net irrigation demand was expressed as a random variable. Niu et al. (2016) advanced an interactive two-stage fuzzy stochastic programming model for crop planning; in which multiple uncertainties in irrigational water availability were handled. CCP is an effective tool for reflecting reliability of satisfying (or risk of violating) system constraints under uncertainty, which permits an in-depth analysis of tradeoffs between system benefit and water shortage risk. Such an analysis could provide more robust strategies for mitigating water shortage risk, especially for some arid regions. Besides, WLNS management may be influenced by some subjective policies (e.g., energy-consumption limitation); price uncertainty is high due to underdeveloped markets and the commodity processing sector (Burrell, 2013). All these difficulties are beyond the capability of CCP. Flexible fuzzy programming (FFP), which can handle uncertainties in association with soft constraints of polices and flexibility on target value of goals, is effective in reflecting the policy variations derived from decision makers (Pishvaee and Khalaf, 2016). Possibilitic fuzzy programming (PFP), coping with imprecise input parameters or the lack of knowledge about parameters, can effectively tackle the uncertainties of price of crop and cost for water pumping.

1.3. Contribution and novelty

The contribution of this study is to develop a possiblilistic-flexible chance-constrained programming (PFCP) method through integrating techniques of PFP, FFP and CCP into a general framework. Each technique offers a unique contribution towards the enhancement of PFCP capabilities of WLNS management under multiple uncertainties. The main novelty and contribution can be listed as: (i) PFCP can be superior to the conventional optimization approaches (e.g., CCP) by introduction of PFP and FFP, dealing with multiple uncertainties expressed as possibilistic distributions, flexible variables and probabilistic distributions; (ii) It can help gain in-depth analysis the tradeoffs between system benefit and risk of violating system constraints, (iii) PFCP will be effectively incorporated into WLNS management for system uncertainty reflection and risk analysis; (iv) irrigation efficiency will be explored in WLNS management for identifying optimal water and land resources allocation patterns.

1.4. Objective

The main objective of this study is to advance such a PFCP approach for managing water-land nexus system with consideration of irrigation efficiencies. The detailed tasks entire: (i) integration of PFP, FFP and CCP into a general framework, (ii) development of PFCP-WLNS management model to attain maximum system benefit under resources and technique constraints, (iii) application of the proposed method to the lower reaches of Amu Darya river basin in Central Asia, (iv) analysis of results of system benefit, crop area, water allocation pattern, and unit water benefit, and (v) identification of the desired schemes under different irrigation efficiencies and uncertainties.

2. Methodology

Chance-constrained programming (CCP) is useful for dealing with random uncertainty and analyzing the risk of violating system constraints (Suo et al., 2017). A CCP model can be formulated as:

$$\mathrm{Max} f = \sum_{i=1}^{m} c_i x_i + \sum_{j=1}^{n} d_j y_j \tag{1a}$$

subject to:

$$a_i x_i \le b_i,\ i = 1, 2, 3, \ldots, m \tag{1b}$$

$$Pr\left[\{t | g_j(t) y_j \le h_j(t)\}\right] \ge 1 - p_j,\ j = 1, 2, 3, \ldots n \tag{1c}$$

$$x_i, y_j \ge 0,\ \forall\ i, j \tag{1d}$$

where x_i and y_j are decision variables; $h_j(t)$ is a set of random elements defined on a probability space T, $t \in T$. The function $Pr()$ represents the probability distribution of random variable $h_j(t)$. Model (1c) consists of fixing a certain level of probability $p_j \in [0, 1]$ for each constraint j and imposing a condition that the constraint is satisfied with at least a probability of 1-p_j (). When the left-hand side coefficient $g_j(t)$ is determined and the right-hand side coefficient $h_j(t)$ is a random variable, an “equivalent” deterministic version can be defined as:

$$g_j(t) y_j \le h_j(t)^{(p_j)},\ \forall\ j \tag{2}$$

where $h_j(t)^{(p_j)} = F^{-1}(p_j)$, given the cumulative distribution function of

$h_j(t)$ (i.e., $F[h_j(t)]$), and the probability of violating constraint j (i.e., p_j). The problem with Model (2) can reflect the case when $g_j(t)$ is deterministic. If both $g_j(t)$ and $h_j(t)$ are uncertain, the set of feasible constraints may become more complicated, and detailed transformation could refer to Li et al. (2009), Simic and Dabic-Ostojic (2017), Li et al. (2018) and Khishandar (2019). Moreover, Model (1) can only reflect the random features of variables, which cannot fully reflect the ambiguous and vagueness in the objective and constraints due to the subjective judgements/experience and insufficient data. Therefore, fuzzy chance-constrained programming is desired for solving such problems. A fuzzy chance-constrained programming model can be formulated as follows:

$$\mathrm{Max} f = \sum_{i=1}^{m} \tilde{c}_i x_i + \sum_{j=1}^{n} \tilde{d}_j y_j \tag{3a}$$

subject to

$$a_i x_i \lesssim b_i,\ i = 1, 2, 3, \ldots, m \tag{3b}$$

$$Pr[\{t | g_j(t) y_j \le h_j(t)\}] \ge 1 - p_j,\ j = 1, 2, 3, \ldots n \tag{3c}$$

$$x_i, y_j \ge 0,\ \forall\ i, j \tag{3d}$$

where c_i, d_j are fuzzy coefficients; $\lesssim$ represents fuzzy inequality which implies that right hand side of constraint is essentially larger than or similar to the left hand side value. Obviously, model (3) can reflect uncertainties expressed as fuzzy sets in constraints and objective function. Flexible fuzzy programming (FFP) can support different kinds of fuzzy numbers as well as various fuzzy ranking methods in soft constraints to defuzzify uncertain parameters. Besides, FFP is effective for dealing with soft constraints and flexibility on target of goals. Based on Pishvaee and Khalaf (2016), a fuzzy number ($\tilde{\xi}$) can be used to show the violation of soft constraints as follows:

$$\mathrm{Max} f = \sum_{i=1}^{m} \tilde{c}_i x_i + \sum_{j=1}^{n} \tilde{d}_j y_j \tag{4a}$$

subject to

$$a_i x_i \le b_i + [\tilde{\xi}_i (1 - \beta)],\ i = 1, 2, 3, \ldots, m \tag{4b}$$

$$Pr[\{t | g_j(t) y_j \le h_j(t)\}] \ge 1 - p_j,\ j = 1, 2, 3, \ldots n \tag{4c}$$

$$x_i, y_j \ge 0,\ \forall\ i, j \tag{4d}$$

$$0 \le \beta \le 1 \tag{4e}$$

where β is indicator of minimum satisfaction level of flexible constraints, which should be carried out subjectively by decision makers. $\tilde{\xi}$ is a triangular fuzzy number, which can be presented by their three prominent points (i.e., $\tilde{\xi} = (\xi_{(1)}, \xi_{(2)}, \xi_{(3)})$) with membership function of:

$$f_A(\xi) = \begin{cases} \frac{\xi - \xi_{i(1)}}{\xi_{i(2)} - \xi_{i(1)}} = f_A^L(\xi),\ \xi_{i(1)} \le \xi \le \xi_{i(2)} \\ \frac{\xi_{i(3)} - \xi}{\xi_{i(3)} - \xi_{i(2)}} = f_A^R(\xi),\ \xi_{i(1)} \le \xi \le \xi_{i(2)} \\ 0, \text{otherwise} \end{cases} \tag{5a}$$

According to the fuzzy ranking method proposed by Yager (1981), $\tilde{\xi}$ can be defuzzied as:

$$\mathbb{R}_{A_i} = \frac{\int_{\xi_{i(1)}}^{\xi_{i(2)}} \xi f_A^L(\xi) d\xi + \int_{\xi_{i(2)}}^{\xi_{i(3)}} \xi f_A^R(\xi) d\xi}{\int_{\xi_{i(1)}}^{\xi_{i(2)}} f_A^L(\xi) d\xi + \int_{\xi_{i(2)}}^{\xi_{i(3)}} f_A^R(\xi) d\xi} = \frac{\int_{\xi_{i(1)}}^{\xi_{i(2)}} \xi \frac{x - \xi_{i(1)}}{\xi_{(2)} - \xi_{(1)}} d\xi + \int_{\xi_{i(2)}}^{\xi_{i(3)}} \xi \frac{\xi_{i(3)} - \xi}{\xi_{i(3)} - \xi_{i(2)}} d\xi}{\int_{\xi_{(1)}}^{\xi_{(2)}} \frac{\xi - \xi_{i(1)}}{\xi_{i(2)} - \xi_{i(1)}} d\xi + \int_{\xi_{i(2)}}^{\xi_{i(3)}} \frac{\xi_{i(3)} - \xi}{\xi_{i(3)} - \xi_{i(2)}} d\xi}$$
$$= \frac{\int_{\xi_{i(1)}}^{\xi_{i(2)}} \xi \frac{\xi - \xi_{i(1)}}{\vartheta_{\xi_i}} d\xi + \int_{\xi_{i(2)}}^{\xi_{i(3)}} \xi \frac{\xi_{i(3)} - \xi}{\vartheta'_{\xi_i}} d\xi}{\int_{\xi_{i(1)}}^{\xi_{i(2)}} \frac{\xi - \xi_{i(1)}}{\vartheta_{\xi_i}} d\xi + \int_{\xi_{i(2)}}^{\xi_{i(3)}} \frac{\xi_{i(3)} - \xi}{\vartheta'_{\xi_i}} d\xi} = \xi_{i(2)} + \frac{1}{3}(\vartheta_{\xi_i} - \vartheta'_{\xi_i}) \tag{5b}$$

where parameters ϑ_ξ and ϑ'_ξ are lateral margins of $\tilde{\xi}$, and defined as:

$$\vartheta_{\xi_i} = \xi_{i(3)} - \xi_{i(2)} \tag{6a}$$

$$\vartheta'_\xi = \xi_{(2)} - \xi_{(1)} \tag{6b}$$

Accordingly, model (4) could be converted as

$$\mathrm{Max} f = \sum_{i=1}^{m} \tilde{c}_i x_i + \sum_{j=1}^{n} \tilde{d}_j y_j \tag{7a}$$

subject to

$$a_i x_i \le b_i + \left(\xi_{i(2)} + \frac{\vartheta_{\xi_i} - \vartheta'_{\xi_i}}{3}\right)(1 - \beta),\ i = 1, 2, 3, \ldots, m \tag{7b}$$

$$Pr[\{t | g_j(t) y_j \le h_j(t)\}] \ge 1 - p_j,\ j = 1, 2, 3, \ldots n \tag{7c}$$

$$x_i, y_j \ge 0,\ \forall\ i, j \tag{7d}$$

$$0 \le \beta \le 1 \tag{7e}$$

The term of $\left(\xi_{(2)} + \frac{\vartheta_\xi - \vartheta'_\xi}{3}\right)(1 - \beta)$ determines the possible violation of each flexible constraint and reflects the decision maker's preference. However, FFP cannot deal with the ambiguous information in decision-making processes (e.g., $\tilde{c}_i$ in the objective) with subjective experience of decision makers. Fortunately, the possibilistic fuzzy programming (PFP) is used to handle the lack of knowledge about the exact values of the model parameters that are modeled by possibilistic distributions with insufficient data and subjective knowledge/experience of the decision maker (Zhou et al., 2013). In the PFP, a symmetric triangular fuzzy number $\tilde{c}_i$ can be determined by a center of c_i^c and a spread w_{c_i}, represented as (c_i^c, w_{c_i}); similarly, $\tilde{d}_j$ can be presented as (d_j^c, w^{d_j}). Since the imprecise coefficients of the objective functions are all restricted by $\tilde{c}_i$ and $\tilde{d}_j$, the objective function is also fuzzy features and its function value f is also symmetric triangular fuzzy numbers based on the extension principle as follows (Inuiguchi and Ramik, 2000):

$$f = \left[\sum_{i=1}^{I} c_i^c x_i + \sum_{j=1}^{J} d_j^c y_j,\ \sum_{i=1}^{I} w_{c_i} x_i + \sum_{j=1}^{J} w^{d_j} y_j\right] \tag{8}$$

Based on the assumption of uncertainty-averse attitude from decision makers and possibility theory, a fractile approach is proposed to tackle the above objective of maximizing the symmetric triangular fuzzy numbers f (). Assume that the decision maker has a great interest in the expected profit (i.e. f) with high certainty degree, maximization of the objective function at λ fractile (the value is u) can be treated as

max$u$

$$Nes\left(\left[\sum_{i=1}^{m} c_i^c x_i + \sum_{j=1}^{m} d_j^c y_j,\ \sum_{i=1}^{n} w_{c_i} x_i + \sum_{j=1}^{n} w^{d_j} y_j\right] \ge u\right) \ge \lambda \tag{9}$$

where λ means necessity fractile or necessity degree, and ranges from 0 to 1, which reflects system benefit preference of decision makers and risk-averse attitude. Selection of λ level depends on decision makers' preferences on imprecise objective. However, λ = 0 indicates risk of violating imprecise objective is the highest and objective would not be satisfied, corresponding to unacceptable solution; λ = 1 indicates risk of violating imprecise objective is the lowest and objective would be fully satisfied with all ambiguous parameters, leading to completely acceptable solution. In practical applications, decision makers prefer that objective should be satisfied under high necessity degree in order to obtain a low objective-violation risk and a high acceptable solution, thus the necessity of the objective should be greater than 0.5 in practices (Zhou et al., 2013; Yu et al., 2019). According to the fractile optimization model proposed by Inuiguchi and Ramík (2000), model (9) can be converted to

$$\sum_{i=1}^{m} c_i^c x_i - \sum_{i=1}^{m} \lambda w_{c_i} x_i + \sum_{j=1}^{n} d_j^c y_i - \sum_{j=1}^{n} \lambda w^{d_j} y_j \ge u \tag{10}$$

Consequently, a possiblistic-flexible chance-constrained programming (PFCP) model is formulated as follows:

$$\max f = \sum_{i=1}^{m} c_i^c x_i - \sum_{i=1}^{m} \lambda w_{c_i} x_i + \sum_{j=1}^{n} d_j^c y_i - \sum_{j=1}^{n} \lambda w^{d_j} y_j \tag{11a}$$

subject to

$$a_i x_i \le b_i + \left(\xi_{i(2)} + \frac{\vartheta_{\xi_i} - \vartheta'_{\xi_i}}{3}\right)(1 - \beta),\ i = 1,\ 2,\ 3,\ ...,m \tag{11b}$$

$$Pr\left[\{t|g_j(t)y_j \le h_j(t)\}\right] \ge 1 - p_j,\ j = 1,\ 2,\ 3,\ ...n \tag{11c}$$

$$x_i,\ y_j \ge 0,\ \forall\ i,\ j \tag{11d}$$

$$0 \le \beta \le 1 \tag{11e}$$

$$0.5 \le \lambda \le 1 \tag{11f}$$

In general, the PFCP model can effectively deal with uncertain parameters presented in terms of fuzzy possibility distributions and random probability distributions; as well as coping with soften constraints and flexible target value of goals.

3. Case study

3.1. Study area

The Amu Darya River is a major tributary of Area Sea Basin in Central Asia, with length of 2400 km and annual mean streamflow of 97.4 km^3. The streamflow is mainly discharged by glacier and snow melting during wet seasons (from April to August). The lower reaches of Amu Darya River basin, divided by Tuyamuyun reservoir, contains three districts (i.e., Karakalpakstan and Khorezm in Uzbekistan, and Dashaoguz in Turkmenistan, as shown in Fig. 1). The lower reaches are dominated by plains and agriculture zones with elevation less than 200 m. The region is characterized by dry continental climate with average temperature of 13.0 °C throughout the year. The mean annual precipitation is less than 100 mm and the potential evapotranspiration is as high as 1150 mm (Awan et al., 2011).

The economy in the lower reaches mainly relies on agricultural practices. The scarce precipitation and excessive evaporation cause that crop cultivation is only feasible through irrigation (Cai et al., 2009). Since 1960, due to expansion of crop area and high water consumption of irrigation (sharing about 90% of total water use), water delivered to the Area Sea basin has sharply decreased, leading to 75% of the surface area being disappeared. Flood and furrow irrigations are the most widespread types of irrigation in the lower reaches; they are characterized by relatively low water-use efficiency (less than 50%) and high waste of water resources (Bekchanov et al., 2015). Such irrigation modes not only have negative impacts on water availability, but also could influence the groundwater table and lead to soil salinization. Land degradation caused by soil salinization has been widespread in this region, where about 15–20% has become unsuitable for cropping (Djumaeva et al., 2013). As food demand is increasing, and water and land resources are continuing to decline, improving water-use efficiency is thus desired for both promoting unit water benefit and making irrigated land resources sustainably arable with less salinization. Agricultural WLNS management in the study area is also subject to various sources of uncertainties and risks. For example, in recent decades, both annual and seasonal agricultural water supplies have decreased; crop market price is fluctuated with economic status and policies; irrigation mainly relies on complicated pumps and canals; electricity for irrigation shares about 25% of the total electricity consumption, which is generated from hydropower that is influenced by random streamflow and changed infrastructure capacity (Djaniberkov and Finger, 2018). All these problems would further amplify the difficulties in WLNS management.

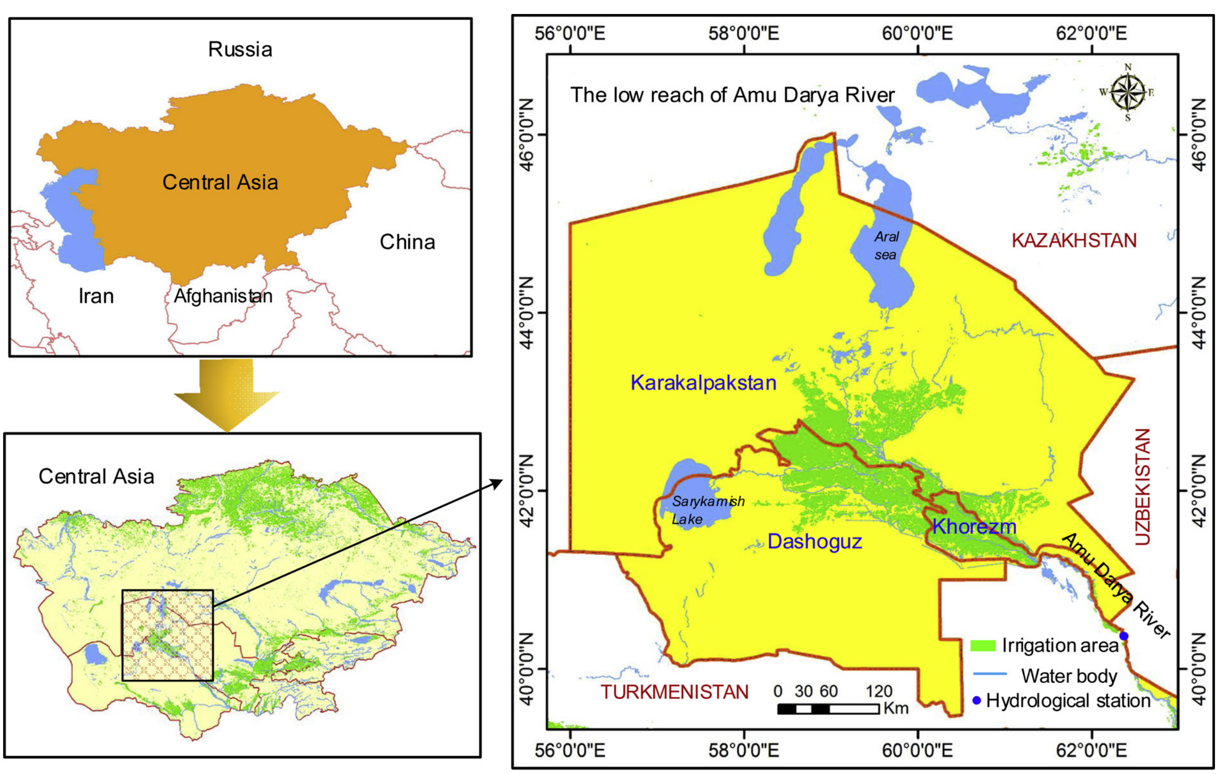

Fig. 1. The study area.

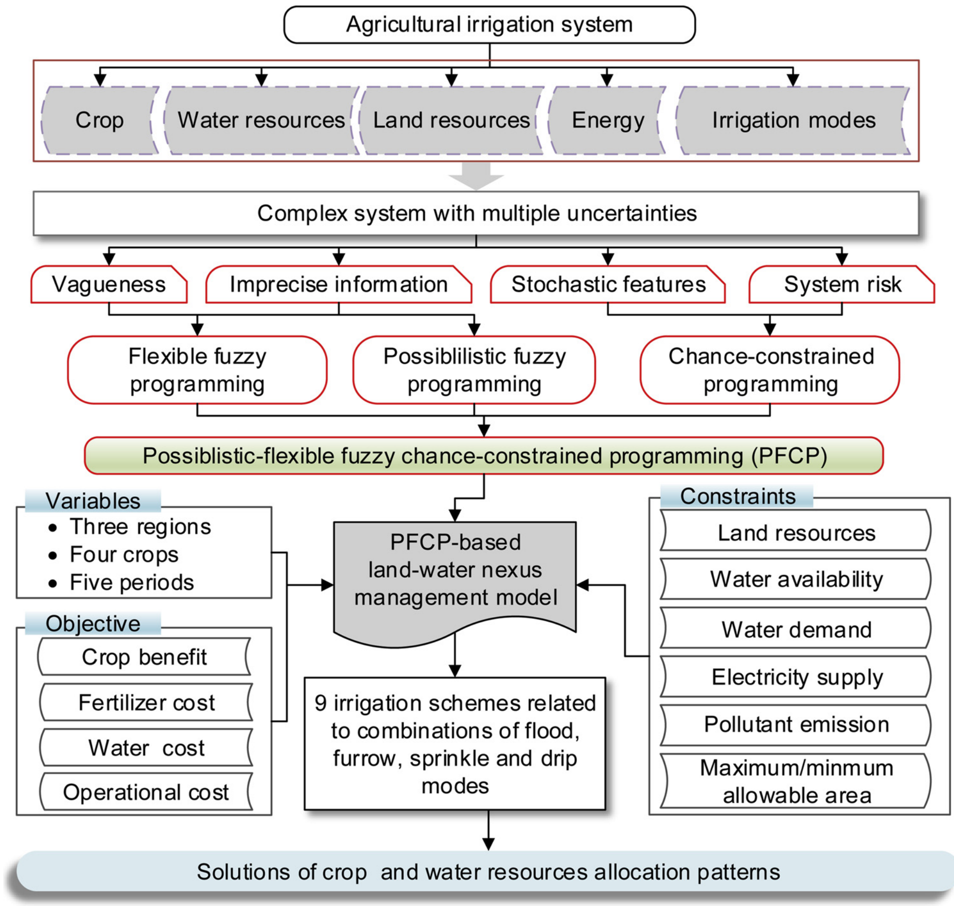

Fig. 2. Framework of PFCP based land-water nexus management model.

3.2. Modeling formulation

A PFCP-based WLNS management (PFCP-WLN) model is formulated that simultaneously allocates water and land resources. The objective is to maximize system benefit subject to a series of constraints (as shown in Fig. 2). The system benefit involves the gross crop incomes, in addition to costs of fertilizer, operation and water pumping. The PFCP-WLN model is:

$$\max f = \sum_{i=1}^{4}\sum_{j=1}^{3}\sum_{t=1}^{5}\widetilde{PC}^{ijt}\times YC^{ijt}\times AC^{ijt} - \sum_{i=1}^{4}\sum_{j=1}^{3}\sum_{t=1}^{5}(\widetilde{PF}^{ijt}\times MF_{ijt}^{\pm}+\widetilde{FC}^{ijt})\times AC^{ijt} - \sum_{i=1}^{4}\sum_{j=1}^{3}\sum_{t=1}^{5}\widetilde{CW}^{ijt}\times SW^{ijt}/\eta_{jt} \quad (12)$$

subject to:

(1) Land area constraint. Land allocated to various crops during the planning horizon must not exceed the net cultivable area of command.

$$\sum_{i=1}^{4} AC^{ijt} \le TAC^{jt},\ \forall\, j,\, t \quad (13)$$

(2) Water resources availability constraint. The total irrigation water of all crops must be not exceed the allowable water availability. The constraint is set as a chance constraint for tackling the random features of water availability.

$$\Pr\left\{\sum_{i=1}^{4}\sum_{j=1}^{3}\sum_{t=1}^{5} SW^{ijt}/\eta_{jt}+\sum_{j=1}^{3}\sum_{t=1}^{5} WOS^{jt}+\sum_{t=1}^{5} EW^{t}\le TW_t\right\}\ge 1-p,\ \forall\, t \quad (14)$$

(3) Irrigation water requirement. The irrigation requirements of all the crops must be fully satisfied from the water withdrawals.

$$\Pr\left\{\sum_{i=1}^{4}\sum_{j=1}^{3}\sum_{t=1}^{5} SW^{ijt}/\eta_{jt}+\sum_{j=1}^{3}\sum_{t=1}^{5} WOS^{jt}+\sum_{t=1}^{5} EW^{t}\le TW_t\right\}\ge 1-p,\ \forall\, t \quad (15)$$

(4) Electricity consumption constraint. The electricity assigned to agricultural irrigation must satisfied with water pumping and conveying demands. Such constraint is set as a fuzzy inequality to reflect policy's subjectivity and decision makers' attitudes towards electricity-supply security.

$$\sum_{i=1}^{4}\sum_{j=1}^{3} PED^{ijt}\times SW^{ijt}/\eta_{jt}\le EP^{jt}+\left(\xi_{(2)}+\frac{\vartheta_{\xi}-\vartheta_{\xi}'}{3}\right)(1-\beta),\ \forall\, j,\, t \quad (16)$$

(5) Pollutant emission. The discharged pollutants (ammonia nitrogen and phosphorus) must not exceed the permissible amounts.

$$\sum_{i=1}^{I}\sum_{j=1}^{J} MF^{ijt}\times AC^{ijt}\times PP_k\times\varphi_{kt}\le TP^{kt},\ \forall\, k,\, t \quad (17)$$

(6) Food security constraints. Lower and upper limits of area under different crops are considered according to local food requirement and socioeconomic issue.

Table 1
Design of irrigation schemes.

Schemes	Description (at the end of planning period)	Efficiency
S1	Scheme 1 with 64% FI, 31% FU, 3% SI and 2% DI	0.51
S2	Scheme 2 with 58% FI, 34% FU, 5% SI and 3% DI	0.53
S3	Scheme 3 with 50% FI, 38% FU, 7% SI and 5% DI	0.55
S4	Scheme 4 with 42% FI, 40% FU, 10% SI and 8% DI	0.58
S5	Scheme 5 with 36% FI, 37% FU, 15% SI and 12% DI	0.61
S6	Scheme 6 with 34% FI, 35% FU, 17% SI and 14% DI	0.62
S7	Scheme 7 with 33% FI, 34% FU, 18% SI and 18% DI	0.63
S8	Scheme 8 with 29% FI, 29% FU, 21% SI and 21%DI	0.67
S9	Scheme 9 with 23% FI, 24% FU, 23% SI and 30% DI	0.71

Note: FI, FU, SI and DI mean flood irrigation, furrow irrigation, sprinkle irrigation and drip irrigation respectively.

Table 3
Water demand of crop (m^3/ha).

		t = 1	t = 2	t = 3	t = 4	t = 5
Cotton	j = 1	9500	9634	9727	9738	9994
	j = 2	9500	9690	9690	9804	9833
	j = 3	9520	9738	9833	9861	9899
Grains	j = 1	6669	6753	6770	6797	6797
	j = 2	5756	5770	5784	5823	5828
	j = 3	5871	5877	5932	5938	5950
Vegetables	j = 1	8549	8549	8579	8629	8636
	j = 2	8142	8142	8146	8171	8178
	j = 3	8386	8386	8415	8426	8456
Others	j = 1	6085	6113	6170	6180	6199
	j = 2	5795	5822	5885	5885	5904
	j = 3	5911	5938	6003	6003	6022

$$AC^{ijt} \geq \lambda_{ijt}^{\min} TAC_{jt}^{\pm}, \forall j, t \tag{18}$$

$$AC^{ijt} \leq \lambda_{ijt}^{\max} TAC^{jt}, \forall j, t \tag{19}$$

(7) Non-negative constraints.

$$AC^{ijt} \geq 0, \forall i, j, t \tag{20}$$

$$SW_{ijt} \geq 0, \forall i, j, t \tag{21}$$

The detailed nomenclatures for variables and parameters are provided in the Appendix A. In this study, nine irrigation schemes under different irrigation modes (flood, furrow, sprinkle and drip irrigations) are designed, corresponding to nine irrigation efficiency levels (i.e., θ) (as shown in Table 1). Besides, five λ levels (0.6, 0.7, 0.8, 0.9 and 1), six β values (0, 0.2, 0.4, 0.6, 0.8 and 1) and four p levels (0.01, 0.05, 0.10 and 0.15) are considered, leading to totally 1080 scenarios. In practical implementation, the solving process of the model can be summarized as: (1) formulate the model; (2) solve the model to obtain a global optimal solution under one λ level; (3) solve each model (under the same λ level) to obtain a global solution under one β level; (4) solve each model (under the same λ and β level) to obtain a global solution under one p level; (5) repeat steps (3) and (4) at each irrigation schemes; and (6) analyze the outputs and provide useful information for decision makers. The computational time for each scenario is less than 1 s on an Intel (R) Core (TM) i7-6700 3.40 GHz CPU with 8.0 GB of memory.

3.3. Data collection and analysis

The planning horizon includes five periods with each of one year (2019–2023). Data related to society, economy, agriculture, water and land resources are obtained from the related literatures, site investigation, statistical yearbooks, and websites. For instance, the prices of crops (as shown in Table 2), the costs of water, fertilizer, and fixed operation, which are expressed as triangular fuzzy numbers, are collected from the expert consultations, survey questionnaires, statistical yearbooks of Uzbekistan and Turkmenistan (2010–2015), and some publications (Khamzina et al., 2008; Singh, 2015). Electricity demand of per unit of water pumping and conveyance are collected from Udias et al. (2018) and adjusted according to local pumping facilities and topographical features. The permissible electricity for irrigation is gained based on the share (about 20%) of total electricity consumption that is acquired from the statistical yearbooks (https://stat.uz/uz). Water demand of each crop (as listed in Table 3) is collected from the website of Food and Agriculture Organization of the United Nations (FAO, http://www.fao.org/faostat). These data are modified according to the local soil feature, precipitation, irrigation requirement, and management policy.

Water availability is estimated by subtracting the volume of water that downstream ecology needs (Q_{down}) from streamflows of Tuyamuyun hydrological station on the website of Central Asia water information (http://www.cawater-info.net). The calculation of Q_{down} is based on the Tenant method that indicates 30% of total water volumes are promised (Sun et al., 2018). Due to the random features, statistical analysis is conducted to obtain the discretization values of water availability with selection of four candidate probability distributions (e.g., normal, gamma, Person-III, and logistic). According to test methods of the maximum likelihood and Chi-square, Gamma distribution with the most perfect performances is used for discretizing values of water availability under different violating probabilities (as shown in Fig. 3).

4. Result analysis

4.1. Uncertainty analysis

Fig. 4 presents system benefits under 1080 scenarios, which range

Table 2
Price of each crop in each period (US$/kg).

		t = 1	t = 2	t = 3	t = 4	t = 5
Cotton	j = 1	(1127,1252,1377)	(1130,1255,1381)	(1154,1283,1411)	(1154,1283,1411)	(1165,1294,1424)
	j = 2	(1134,1260,1386)	(1137,1264,1390)	(1159,1288,1416)	(1165,1294,1424)	(1180,1311,1442)
	j = 3	(1128,1253,1379)	(1128,1253,1379)	(1134,1260,1386)	(1134,1260,1386)	(1150,1277,1405)
Grain	j = 1	(399, 444, 488)	(403, 447, 492)	(408, 453, 498)	(408, 453, 498)	(413, 459, 505)
	j = 2	(387, 430, 473)	(388, 431, 474)	(395, 439, 483)	(397, 442, 486)	(403, 447, 492)
	j = 3	(385, 428, 470)	(385, 428, 470)	(387, 430, 473)	(387, 430, 473)	(392, 436, 479)
Vegetable	j = 1	(511, 567, 624)	(516, 573, 630)	(520, 578, 636)	(525, 584, 642)	(530, 589, 648)
	j = 2	(518, 575, 633)	(523, 581, 639)	(528, 586, 645)	(533, 592, 651)	(538, 598, 657)
	j = 3	(512, 569, 626)	(517, 575, 632)	(522, 580, 638)	(527, 586, 644)	(532, 591, 650)
Others	j = 1	(542, 603, 663)	(552, 613, 675)	(557, 619, 681)	(562, 624, 687)	(567, 630, 693)
	j = 2	(548, 609, 669)	(558, 620, 682)	(563, 625, 688)	(568, 631, 694)	(573, 636, 700)
	j = 3	(542, 602, 662)	(552, 613, 674)	(557, 618, 680)	(561, 624, 686)	(566, 629, 692)

Note: The data is presented in triangular fuzzy sets (A, B, C), where B is the center value, and (A + C)/2 is the radial value of spread.

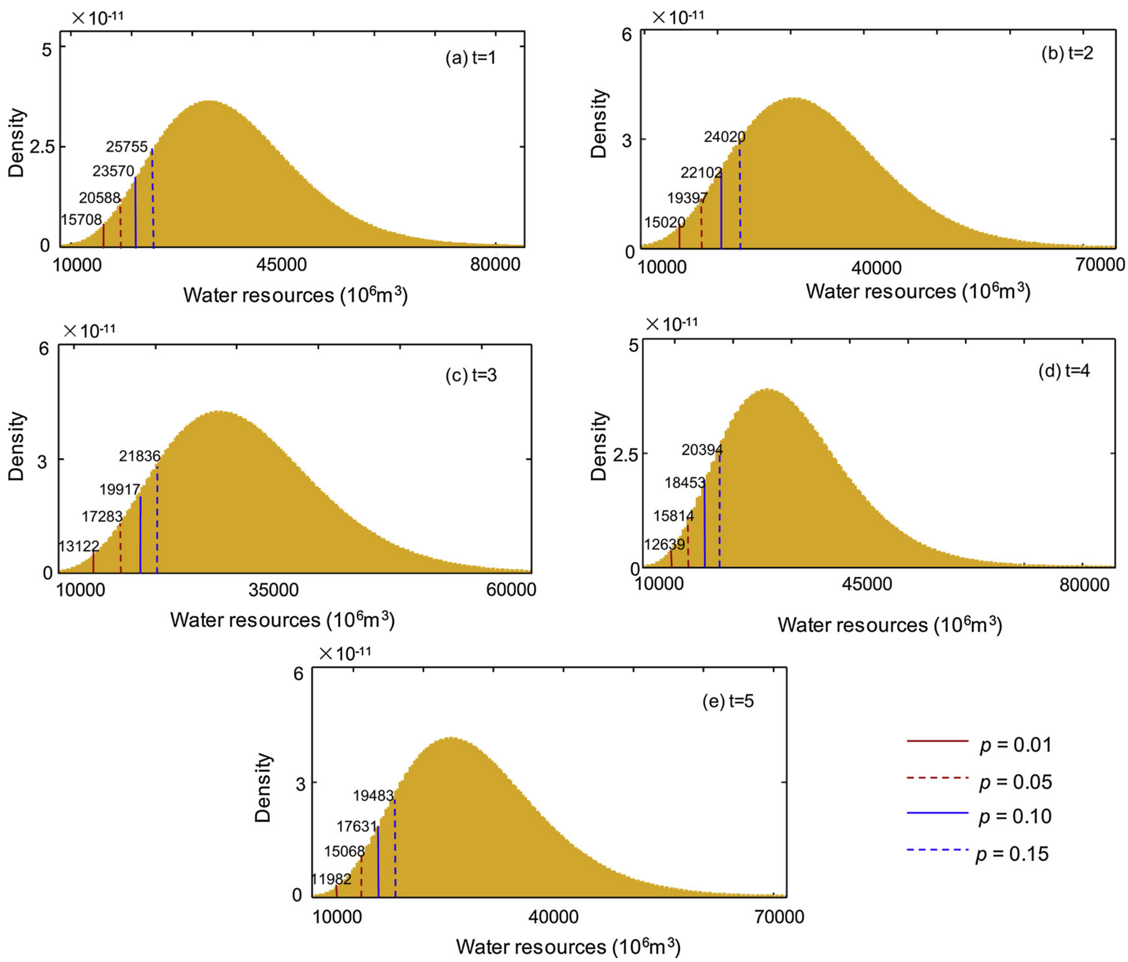

Fig. 3. Probability distributions of water resources in different periods (10^6 m^3).

from US\$5,648 × 10^6 to US\$11,545 × 10^6. The highest system benefit occurs under irrigation scheme 9 (S9) when $\lambda = 0.6$, $\beta = 0$, and $p = 0.15$, and the lowest system benefit corresponds to irrigation scheme 1 (S1) when $\lambda = 1$, $\beta = 1$, $p = 0.01$. In detail, system benefit would decrease along with λ level. This is because λ means decision maker's risk-averse attitude to objective; higher λ level leads to decreased objective-violation risk and descend system benefit. System benefit would decrease with β level. High β level would toward the decision maker's desire to achieve the maximized system benefit with low violation degree (i.e., high satisfactory degree) in soft constraints, thus resulting in a strict electricity consumption control. Besides, when λ is 0.6, β is 0 under S1, the system benefit would be US\$5,892 × 10^6 under $p = 0.05$ and US\$10,792 × 10^6 under $p = 0.15$; a higher p level associated with increased violation of risk results in a higher system

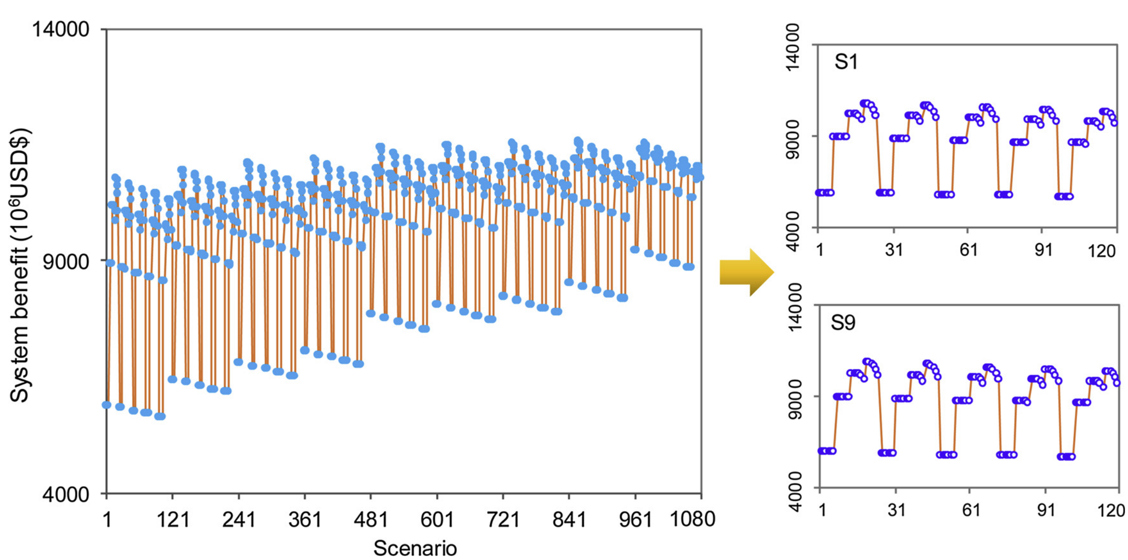

Fig. 4. System benefits under different scenarios.

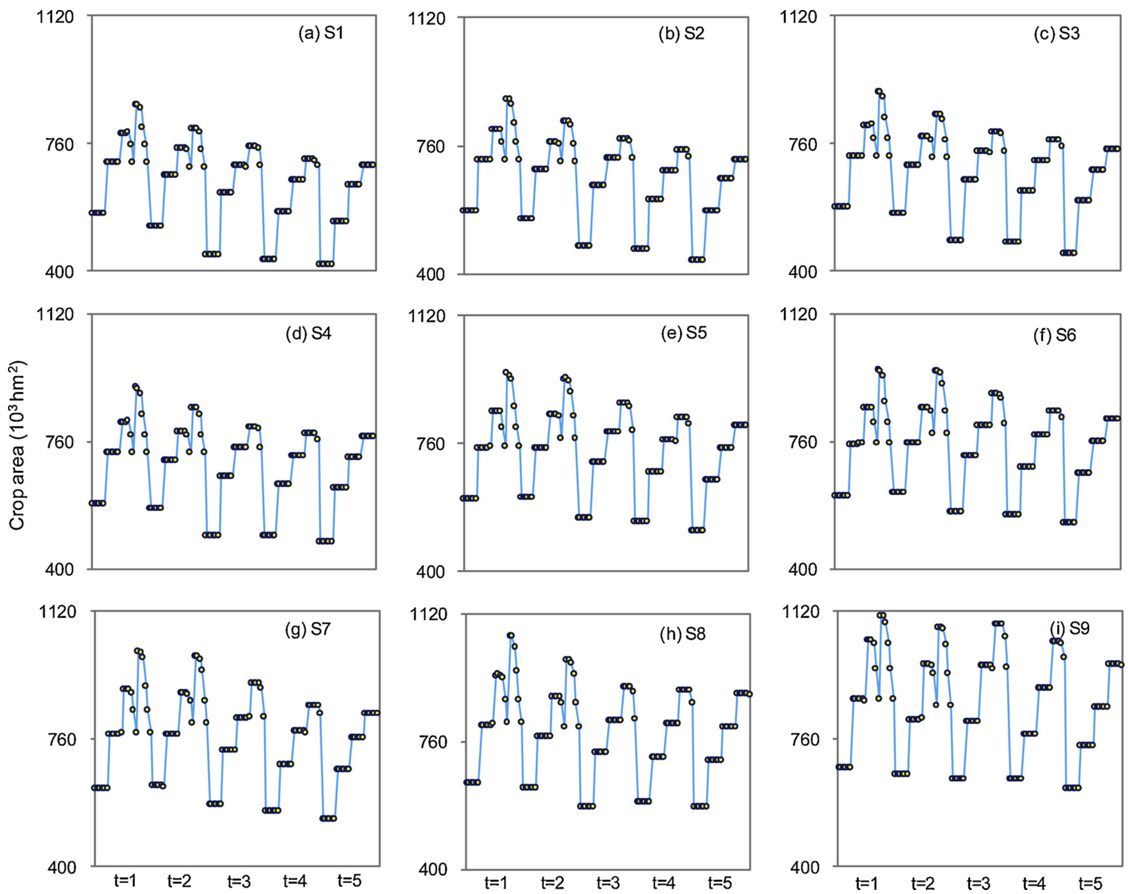

Fig. 5. Total crop areas under different scenarios.

benefit. By varying the p level, decision makers can acquire the compromise between system benefit and system-failure risk. In general, higher p, lower λ, and lower β can lead to higher system benefit; however, this variation also corresponds to increased risk level (i.e., declined system reliability).

Fig. 5 presents the total crop area in the lower reaches, which indicates that total crop area is highly related to random water availability and decision maker's satisfactory degree to electricity consumption. As shown in Fig. 5a (under S1), when $\beta = 0$, the total crop area would be 565×10^3 ha under $p = 0.01$, and 868×10^3 ha under $p = 0.15$, meaning that higher p level results in an increased crop area due to ascended irrigation water availability. Besides, when $p = 0.15$, the total crop area would decrease from 868×10^3 ha ($\beta = 0$) to 708×10^3 ha ($\beta = 1$). Higher β means lower degree of violating electricity consumption constraint, leading to less water being pumped and converted. However, when p levels are 0.01 and 0.05, total crop area would not be affected by β level, signifying that the predetermined lowest agricultural electricity consumption could fully satisfy pumping and conveyance when water availability is low.

4.2. Impacts of irrigation efficiency

Irrigation efficiency changes would alter crop area, crop plating pattern and unit water benefit. As shown in Fig. 5, the maximum total crop area would increase from 868×10^3 ha (S1) to 1108×10^3 ha (S9) in period 1, illustrating that irrigation efficiency promotion has a positive effect on crop area. This is because irrigation efficiency promotion would reduce water demand of per unit land. Fig. 6 presents the proportion of different crops under the nine irrigation schemes. Results indicate that enhancement of irrigation efficiency would impact cropping patterns. For example, when $p = 0.01$, the proportion of vegetable and other crops would dramatically increase along with irrigation efficiency; this is because water would be first delivered to vegetables and other crops due to their high profit and low water demand after the minimum area requirements of cotton and grain are met. When $p = 0.15$, cotton proportion would ascend from 24.0% to 46.2% in Karakalpakstan and from 46.6% to 51.3% in Dashoguz along with irrigation efficiency. After irrigation scheme 6 (irrigation efficiency is 0.62), the proportion change trends get slight. Results also imply that different districts should adopt varied irrigation schemes according to local economic conditions, agricultural policies, and irrigation infrastructures.

In a context of scarcity of land and water resources, recognition of unit water benefit is one of the management alternatives. In this study, unit water benefit, referring to the net system benefit produced by per unit water resources, is evaluated under different irrigation schemes. As shown in Fig. 7, unit water benefit ranges from 0.15 US\$/m^3 (under S1) to 0.24 US\$/m^3 (under S9) when $\beta = 1$ and $p = 0.01$, meaning that advancement of irrigation modes (e.g., sprinkle and drip) has a positive effect on unit water benefit. Comparably, when $p = 0.15$, unit water benefit would change from 0.18 US\$/m^3 under S1 to 0.20 US\$/m^3 under S9. Moreover, unit water benefit would reduce with increased water resources availability when irrigation efficiency is greater than 0.61 (i.e., S5), suggesting that advancement of irrigation modes are more effective under the condition of extreme water resources scarcity. Accordingly, S5 is an effective option for pursuing balance among unit water benefit and water-land allocation patterns in responding to changed water availabilities. Unit water benefit also shows relation to varied water availabilities and electricity consumptions, which are corresponding to varied land and water allocation patterns. Generally, comprehensive agricultural management strategies (e.g., the advancement of irrigation modes as well as the optimization of water and land

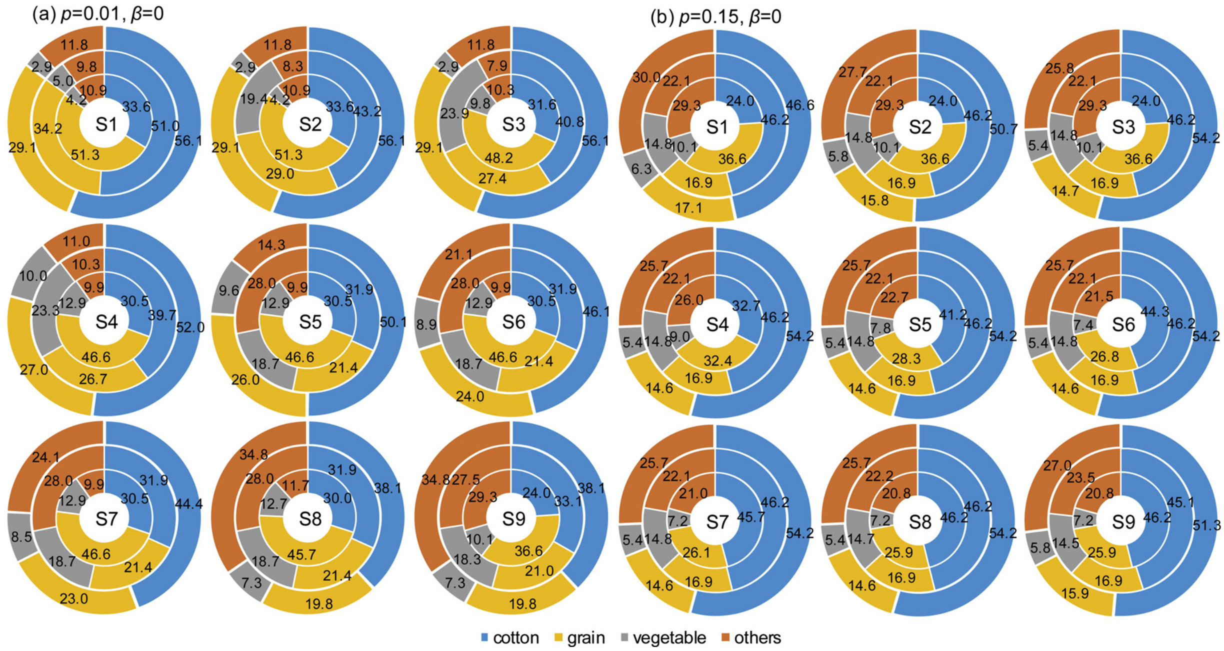

Fig. 6. Proportion (100%) of each crop under different irrigation schemes in period 5 [the circles from the inside to the outside represent Karakalpakstan, Khorezm and Dashoguz, respectively].

allocation patterns) need to be implemented according to the real-world conditions (e.g., water availability and electricity consumption).

4.3. Water-land nexus analysis

Fig. 8 illustrates the water-allocation alternatives for each region and crop. Results show that water resource-allocation alternatives are closely related to cropping patterns. In detail, vegetables are of the

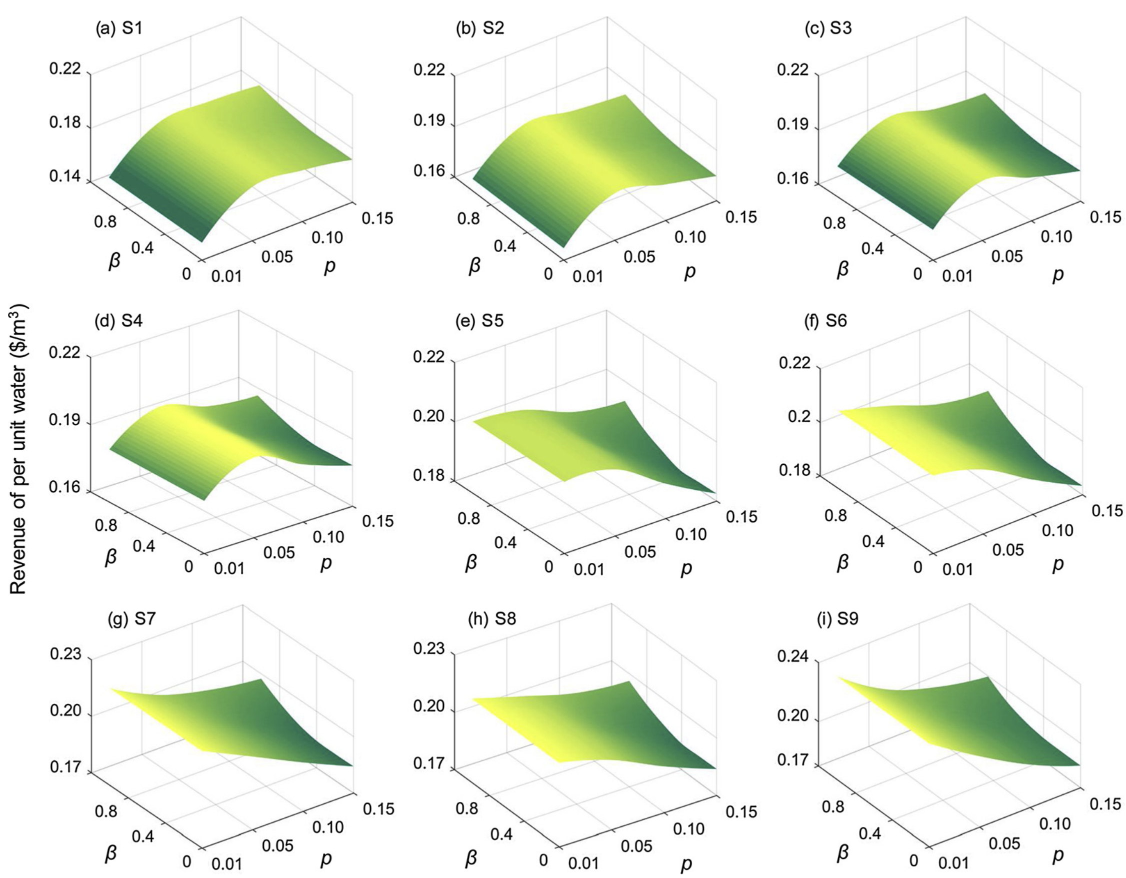

Fig. 7. Unit water benefit under different irrigation schemes (US$/$m^3$).

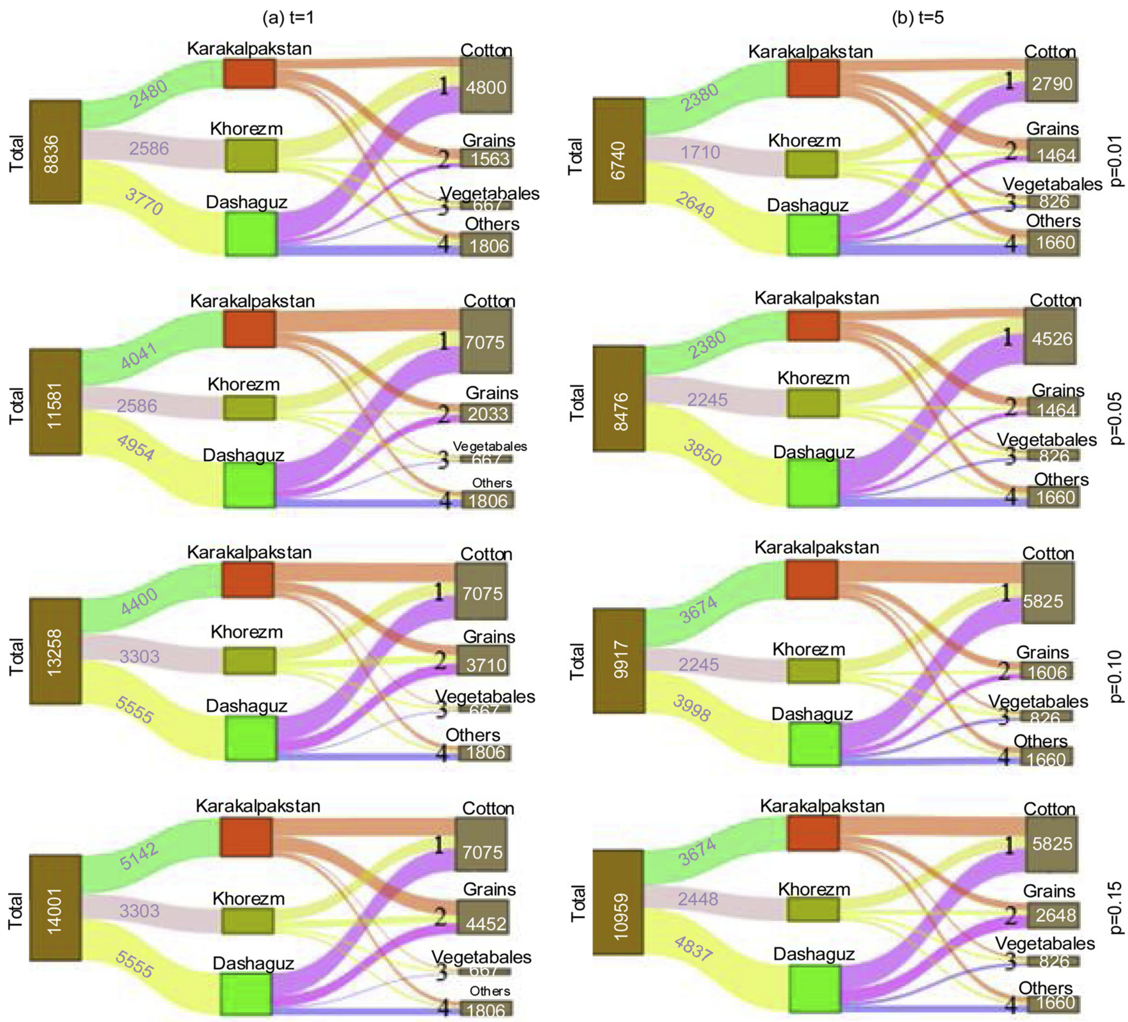

Fig. 8. Figure 8. Water allocation patterns to different crops (10^6 m^3).

highest priority to water resources after food security needs are met; this is because vegetables possess higher prices and lower resources requirements. In period 1, water resources allocated to vegetables and others are 667 × 10^6 m^3 and 1806 × 10^6 m^3, respectively. In period 5, the two values would be 826 × 10^6 m^3 and 1660 × 10^6 m^3. Water resources are then diverted to cotton to meet policy requirements. Results show that the volumes of water delivered to cotton are the largest in all regions, implying that cotton keeps the major water consumer in the lower reaches of Amu Dray river basin. Comparably, water resources allocated to grains heavily depends on the water availability. Even under the maximum system violation level (corresponding to maximum water availability), water demands of the maximum grain requirements still could not be met. Polices and strategies should be made not only to guarantee the basic food requirement, but also to promote water saving measures, especially for grains.

Fig. 9 depicts the effect of water availability on each crop area under S6. The results indicate that cropping pattern would vary across different water availabilities. For example, cotton in Karakalpakstan at the end of planning horizon would increase from 53 × 10^3 ha (p = 0.01) to 144 × 10^3 ha (p = 0.15), illustrating that increasing water availability related to supply management strategy would be beneficial for land expansion. Moreover, the impacts of water availability on crop area of Khorezm are less obvious than that in other districts. This may because water resources would be firstly delivered to Khorezm due to its location (upper stream) and economic status (possessing relatively completed agricultural infrastructures). When water resources is very limited (e.g., p is less than 0.05), the crop area may be far lower than the maximum requirements, which may bring food crisis. Strategies should be implemented for mitigating the negative impacts, such as using the groundwater conjunctively with good quality canal water, adopting salt- and drought-tolerant crops, and matching water supply more closely with demand.

5. Discussion

Results obtained demonstrated that variations of irrigation mode, water availability, and electricity consumption have obvious effects on water and land resources allocation patterns. Some other research works related to agricultural management also shown that cropping area would increase along with advancement of irrigation mode and increase of water availability (Bhaduri and Manna, 2014; Das et al., 2015; Niu et al., 2016; Kisekka et al., 2019). Such consistence further validates the applicability of PFCP in exploring the impacts of irrigation efficiency on WLNS management. Besides, differences are avoidable due to the variations in data sources, models, and research objectives. For example, the optimized total crop area in the lower reaches of Amu Darya River basin ranges from 840 to 985 × 10^3 ha by Bekchanov et al. (2016) under normal water availability, which is larger than that (ranging from 418 to 696 × 10^3 ha) by PFCP-WLNS under 15% of the cumulative distribution probability of water availability. Such difference can be reasoned by the variations in water availabilities and can be acceptable. Besides, the system benefit is about 9100 × 10^6 US$/year

Fig. 9. Areas of crops corresponding to varied water availabilities under irrigation scheme 5.

in the whole Amu Darya River basin acquired by Jalilov et al. (2018), which is about 5–7 times larger than [1110, 2300] × 10^6 US$/year by PFCP-WLNS (only three districts are considered). System benefit ([250, 510] × 10^6 US$/year) by Bekchanov et al. (2016) shows smaller than that by PFCP-WLNS; this is because raw cotton price is adopted by Bekchanov et al. (2016), which is about three times cheaper than that by PFCP-WLNS (considering the fiber cotton price). The differences in system benefit is mainly derived from diversified study area, proposed models and inputted parameters. Comparably, uncertainty analysis is conducted in this study which can effectively tackle subjectivity, random features, and vagueness in the system, providing reliable information of agricultural system. Generally, the results obtained are acceptable for supporting water-land nexus system management.

PFCP-WLNS has provided useful insights on irrigation efficiency's impacts on water and land resources management. Solutions are valuable for generating alternatives and thus help decision makers to identify desired water-land nexus management policies under multiple uncertainties. However, in Amu Darya River basin, water-land nexus management strategies may be impacted by soil salinization due to changed groundwater table; salinity leaching is an important practice outside the crop growth season, without consideration of which would leading to underestimation of the water demands and ignorance salinity's effect on crop yield. Therefore, it is desired that water uses for salinity should be investigated in the future research works.

6. Conclusions

In this study, a possibilistic-flexible chance-constrained programming (PFCP) method has been developed through integrating possibilistic fuzzy programming, flexible fuzzy programming, and chance-constrained programming within a general framework. The developed PFCP method can (i) deal with uncertainties expressed as possibilistic distributions, flexible variables and probabilistic distributions; (ii) reflect decision makers' risk-averse attitude by introducing necessity degrees of the objective function, and (iii) help examine the reliability of satisfying (or risk of violating) system constraints. Then, a PFCP based water-land nexus model has been formulated for managing water-land nexus system of the lower reaches of Amu Darya River basin. Totally 1080 scenarios related to different irrigation schemes, water availabilities, electricity consumptions, and risk-reverse attitudes to objective have also been designed for examining irrigation efficiency's impacts on water-land nexus system management.

Solutions for system benefit, crop area and water allocation alternatives have been generated under multiple uncertainties and irrigation schemes. Results show that (i) system benefit and total crop area increase along with water availability and electricity consumption, accompanying with increased of system risk level; (ii) water and land resources would be firstly allocated to vegetables after minimum food requirements are met due to its higher profit; (iii) the lowest unit water benefit (0.15 US$/m^3) and the maximum (0.24 US$/m^3) both occur under the lowest water availability level (p = 0.01), implying that

improvement of irrigation efficiency is more effective under the condition of extreme water resources scarcity; (iv) irrigation mode with efficiency of about 0.61 is an effective option in adaptation to changed water availabilities, which is beneficial for pursuing balance between water and land relationships, as well as providing compromise between system benefit and risk level. Generally, advancement of irrigation measures, as well as optimization water and land allocation patterns are effective management strategies in responding to changed real-world conditions (e.g., water availability, electricity consumption, and market price). These findings can help decision makers reallocate water and land resources effectively and implement irrigation mode appropriately.

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Appendix A

Nomenclature

i	Crop type (i = 1,2,3,4, representing cotton, grains, vegetable and others)
j	District (j = 1,2,3, representing Karakalpakstan, Khorezm and Dashaguz)
t	Planning period, t=1,2,3,4,5
f	System benefit (US$)
AC_{ijt}	Area of crop i in district j in period t (ha)
SW_{ijt}	Water allocated to crop i in district j in period t (m^3)
PC_{ijt}	Price of per unit of crop i in district j in period t (US$/kg)
YC_{ijt}	Yield of crop i in district j per area of crop in period t (kg/ha)
PF_{ijt}	Unit cost of fertilizer of crop i in district j in period t (US$/kg)
MF_{ijt}	The quantity of fertilizer applied to crop i in district j in period t (kg/ha)
FC_{ijt}	Operational cost (including the labor, machinery and seeds) for the crop i in district j in period t (US$/ha)
CW_{ijt}	Amount of electricity for water pumping and conveyance for crop i in district j in period t (KWh/m^3)
TAC_{jt}	The total permissible crop area in district j in period t (ha)
WOS_{jt}	Water uses for other sectors (e.g., municipal and industrial sectors) in district j in period t (m^3)
TW_t	Total availability of water resources for irrigation in period t (m^3)
EP_{jt}	Permissible electricity for irrigation in district j in period t (KWh)
WPC_{ijt}	Water demand for crop i in district j in period t (m^3/ha)
η_{jt}	Canal transmission efficiency in district j in period t
θ_{jt}	Infield irrigation efficiency in district j in period t
PP_{kt}	Proportion of pollutant k in fertilizer in period t
φ_{kt}	Loss rate of pollutant k in period t
TP_{kt}	Total permissible discharge of pollutant k in period t
λ_{ijt}^{min}	The minimum ratio of area of crop i in district j in period t
λ_{ijt}^{max}	The maximum ratio of area of crop i in district j in period t

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